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Evaluation of Matrix Factorisation Approaches for Muscle Synergy Extraction

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Abstract

The muscle synergy concept provides a widely-accepted paradigm to break down the complexity of motor control. In order to identify the synergies, different matrix factorisation techniques have been used in a repertoire of fields such as prosthesis control and biomechanical and clinical studies. However, the relevance of these matrix factorisation techniques is still open for discussion since there is no ground truth for the underlying synergies. Here, we evaluate factorisation techniques and investigate the factors that affect the quality of estimated synergies. We compared commonly used matrix factorisation methods: Principal component analysis (PCA), Independent component analysis (ICA), Non-negative matrix factorization (NMF) and second-order blind identification (SOBI). Publicly available real data were used to assess the synergies extracted by each factorisation method in the classification of wrist movements. Synthetic datasets were utilised to explore the effect of muscle synergy sparsity, level of noise and number of channels on the extracted synergies. Results suggest that the sparse synergy model and a higher number of channels would result in better estimated synergies. Without dimensionality reduction, SOBI showed better results than other factorisation methods. This suggests that SOBI would be an alternative when a limited number of electrodes is available but its performance was still poor in that case. Otherwise, NMF had the best performance when

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the number of channels was higher than the number of synergies. Therefore, NMF would be the best method for muscle synergy extraction.

Keywords: Muscle synergy, Matrix factorisation, Surface electromyogram, Non-negative matrix factorisation, second-order blind identification, Principal component analysis, Independent component analysis.

1. Introduction

1.1. Muscle synergy

“How does the central nervous system (CNS) control body movements and posture?” This question has been discussed for over a century with no conclusive answer. The coordination of muscles and joints that accompanies movement requires multiple degree of freedoms (DoFs). This results a high level of complexity and dimensionality [1]. A possible explanation to this problem considers the notion that the CNS constructs a movement as a combination of small groups of muscles (synergies) that act in harmony with each other, thus reducing the dimensionality of the problem. This idea could be traced to the first decades of the twentieth century [2] and has been formulated and developed through the years [3, 4, 5] to reach the Muscle Synergy hypothesis [6, 7, 8]. The muscle synergy concept posits that the CNS achieves any motor control task using a few synergies combined together, rather than controlling individual muscles. Although the muscle synergy hypothesis is criticized for being very hard to be falsified [9], a repertoire of studies have provided evidence and support for it. Those pieces of research could be categorized into two main categories: direct stimulation and behavioural studies.

The stimulation approaches were conducted by exciting the CNS at different locations to study the resulting activation pattern. Earlier studies focused on the organization of motor responses evoked by micro-stimulation of the spinal cord of different vertebral species, such as frogs [3, 4, 5, 10, 11], rats [12] and cats [13]. They revealed that the responses induced by simultaneous stimulation of different loci in the spinal cord are linear combinations of those induced by

25 separate stimulation of the individual locus. Those findings were supported
26 by another direct stimulation studies where a relatively long period of electric
27 stimulation applied to different sites in the motor cortex resulted in complex
28 movements in rats [14], prosimians [15] and macaques [16, 17]. The chemical
29 micro-stimulation has been used through N-methyl-D-aspartate iontophoresis
30 injected into the spinal cord of frogs which evoked an electromyographic (EMG)
31 patterns that could be constructed as a linear combination of a smaller group
32 of muscle synergies [7].

33 Similarly, the behavioural studies rely on recording the electrical activity of
34 the muscles (electromyogram, EMG) during a specific task (or tasks) or natural
35 behaviour. Then, a number of synergies is extracted from the signals using com-
36 putational techniques. The identified synergies should be able to describe the
37 recorded signal for the related task or behaviour. Studies have been carried out
38 on cats where four muscle synergies were sufficient to reproduce 95% of postural
39 hind-limb muscles response data [18] and five synergies accounted for 80% of
40 total variability in the data [19]. Similar research on monkeys during grasping
41 activity showed that three muscle synergies accounted for 81% of variability [16].
42 In humans, muscle synergies were identified from a range of motor behaviours
43 [20, 21] with the ability to describe most of the variability in EMG signals. In
44 addition, other studies show that complex motor outputs such as upper limb
45 reaching movements [22], cycling [23, 24] and human postural control [25] are a
46 result of the combination of few muscle synergies.

47 In the recent years, many studies applied the muscle synergy concept to anal-
48 yse and study body movements and muscle coordination in diverse applications.
49 For instance, it has been used to establish the neuromuscular system model [26].
50 Moreover, the hypothesis has been used in many clinical applications [27] in ad-
51 dition to several biomechanical studies such as walking and cycling [28, 29].
52 The extracted synergies are utilised in prosthesis control through classification
53 [30, 31] and regression [32].

54 1.2. Mathematical models for muscle synergy

55 In all studies, the muscle synergies are estimated from the recorded electri-
56 cal activity of the muscle. Signals are either collected using surface EMG or
57 invasively using needle EMG. Then, the EMG recordings needs to be modelled
58 in order to compute the muscle synergies.

59 Two main muscle synergy models have been proposed: the time invariant
60 or synchronous model [6, 7] and the time-varying or asynchronous model [33,
61 8]. The electrical activity for single muscle or channel $\mathbf{m}(t)$ is a vector that
62 could be expressed according to the time-invariant model as a combination of
63 synchronous synergies \mathbf{s} (scalar values activated at the same time) multiplied by
64 a set of time-varying coefficients or weighting functions \mathbf{w} as shown in equation
65 1

$$\mathbf{m}(t) = \sum_{i=1}^{i=r} s_i \mathbf{w}_i(t) \quad (1)$$

66 where r is the number of synchronous synergies. Since synergies contribute
67 to each muscle activity pattern with the same weighting function $\mathbf{w}_i(t)$, the
68 synergy model is synchronous without any time variation.

69 On the other hand, the time-varying synergies are asynchronous as they
70 are compromised by a collection of scaled and shifted waveforms, each one of
71 them specific for a muscle or channel. Thus, the muscle activity $\mathbf{m}(t)$ can be
72 described according to the asynchronous model with a group of time-varying
73 synergy vectors scaled and shifted in time by c and τ , respectively, as shown in
74 equation 2.

$$\mathbf{m}(t) = \sum_{i=1}^{i=r} c_i \mathbf{s}_i(t - \tau_i) \quad (2)$$

75 In this case, the model is capable of capturing fixed relationships among the
76 muscle activation waveforms across muscles and time. By means of comparison,
77 time-invariant synergies can acquire the spatial structure in the patterns but any
78 fixed temporal relationship can be recovered only indirectly from the weighting
79 functions associated with its synchronous synergy.

80 Although the time-varying model provides a more parsimonious representa-
81 tion of the muscle activity compared to the time-invariant model, some studies

82 have shown evidence that the muscle synergies are synchronised in time [34, 10].
83 Therefore, most recent muscle synergies studies apply the time-invariant model
84 for synergy extraction. This is done by using matrix factorization techniques on
85 multichannel EMG activity to estimate the muscle synergies and their weighting
86 functions.

87 *1.3. Comparison of Matrix factorization techniques*

88 According to the time-invariant model, the estimation of muscle synergies
89 (spatial profile) and their weighting functions (temporal profile) from a multi-
90 channel EMG signal is a blind source separation (BSS) problem. This problem
91 is approached by matrix factorisation techniques to estimate the set of basis
92 vectors (synergies). Various matrix factorisation algorithms have been applied
93 based on different constraints. The most commonly used factorisation tech-
94 niques to extract synergies for myoelectric control and clinical purposes are
95 principal component analysis (PCA) [35] which was applied in [36], indepen-
96 dent component analysis (ICA) [37] that was used in [30] and [38], in addition
97 to non-negative matrix factorization (NMF) [39] which have been used in [40, 32]
98 and [41].

99 In this paper, these three techniques are compared among themselves and to
100 second-order blind identification (SOBI) [42], a technique which has not been
101 used for muscle synergy estimation previously. A first evaluation of the matrix
102 factorisation algorithms for muscle synergy extraction was reported in 2006 [43]
103 where the algorithms were tested with simulated data under different levels and
104 kinds of noise and they were applied on real data to show the similarities be-
105 tween their estimated synergies. A more recent study [44] used joint motion
106 data to evaluate kinematics and muscle synergies estimated by PCA, ICA and
107 NMF using the quality of reconstructing the data by synergies as a metric for
108 evaluation. Here, we are concerned with nature and number of muscle synergies
109 and the factors that affect their quality which have not been discussed by those
110 studies. The sparsity of synergies is investigated where synthetic sparse and
111 non-sparse synergies are compared to study their effect on the matrix factorisa-

112 tions. Moreover, the ratio between number of channels and synergies (dimension
113 reduction ratio) is studied. Those comparisons are carried out under different
114 noise levels to show the robustness of factorisation methods to noise. In addition,
115 synergies extracted from a real dataset by the four matrix factorisation
116 techniques were used to classify between wrist movements. The classification
117 accuracy was used as a metric in the factorisation methods comparison. We
118 aim to compare current matrix factorisation techniques in addition to SOBI
119 and investigate the factors that affect the quality of their extracted synergies
120 such as sparsity and channel/synergy ratio.

121 **2. Methods**

122 *2.1. Real dataset*

123 We used the Ninapro first dataset [45, 46] which consists of recordings for
124 53 wrist, hand and finger movements. Each movement/task has 10 repetitions
125 from 27 healthy subjects. The dataset contains 10-channel signals rectified by
126 root mean square and sampled at 100 Hz as shown in Figure 1. The real dataset
127 is used in the comparison between matrix factorisation techniques. Moreover,
128 it is used as a part of the synthetic data creation as discussed in 2.2.

129 For the real data comparison, the three main degree of freedoms (DoF) in-
130 vestigated for the wrist motion are wrist flexion and extension (DoF1), wrist
131 radial and ulnar deviation (DoF2), and wrist supination and pronation (DoF3).
132 Wrist movement through these three degrees of freedom are essential for pros-
133 thetic control [47]. Thus, they may highlight the application of muscle synergies
134 in myoelectric control.

135 *2.2. Synthetic data*

136 The performance of each matrix factorisation algorithm was tested using
137 synthetic datasets as ground truth. Since the studies [34, 10] showed an evi-
138 dence that the muscle synergies are synchronised in time, the data was generated
139 according to the time-invariant model [6] in which EMG activity for j^{th} -channel

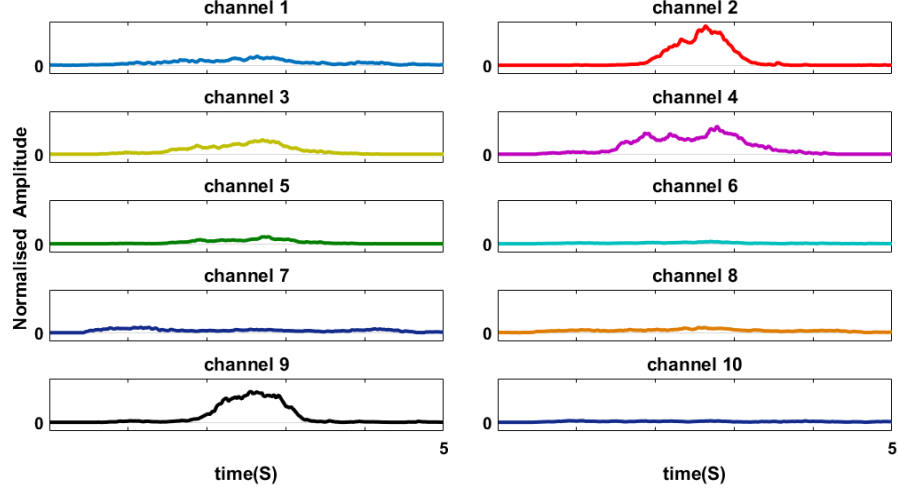


Figure 1: Example of 10-channel EMG envelopes recorded during wrist extension movement for 5 s of Subject 4/repetition 1 (the amplitude is normalised only in figure to highlight the differences between channels).

140 is the summation of its coefficients in each synergy (s_{ij}), weighted by the re-
 141 spective weighting function ($\mathbf{w}_i(t)$), as the following:

$$\mathbf{m}_j(t) = \sum_{i=1}^{i=r} s_{ij} \mathbf{w}_i(t) + g(\epsilon) \quad (3)$$

142 where $\mathbf{m}_j(t)$ is the simulated EMG data over channel j , while ϵ is a Gaussian
 143 noise vector and $g(x)$ is the Heaviside function used to enforce non-negativity.
 144 For m -channel data, this model could be expanded into its matrix form. In this
 145 case, the synthetic EMG data \mathbf{M} is a matrix with dimensions (m channels \times n
 146 samples) as

$$\mathbf{M}_{(m \times n)} = \mathbf{S}_{(m \times r)} \times \mathbf{W}_{(r \times n)} + g(\mathbf{E}) \quad (4)$$

147 where r is the number of synergies ($r < m$) and \mathbf{E} is the matrix form of the
 148 Gaussian noise vector ϵ for all channels. \mathbf{S} ($m \times r$) and \mathbf{W} ($r \times n$) are the
 149 synergy matrix and weighting function matrix form, respectively.

150 In order to generate a synthetic EMG signal that mimics the real EMG
 151 data and carries the synergistic information, the three elements in equation 4

152 should be designed so that they reflect real activities under diverse assumptions.
 153 The synergy matrix $\mathbf{S}_{(m \times r)}$ was assigned a non-negative random values between
 154 $[0,1]$ to retain the additive nature of synergies, while each weighting (activation)
 155 function $\mathbf{W}_{(r \times n)}$ is a real EMG envelope randomly assigned from the Ninapro
 156 dataset from different subjects and movements. This approach based on real
 157 data was chosen to ensure that the generated signal retains the statistical prop-
 158 erties of the EMG signal rather than assigning randomly generated signals for
 159 the weighting function as done in the past [43]. Finally, the non-negative part
 160 of the Gaussian noise is applied to the mixture by the Heaviside function $g(\mathbf{E})$.
 161 An example of the generated synthetic EMG signal is shown in Figure 2.

162 The synthetic signals were generated with different settings to compare the
 163 factorisation methods under various conditions. In all settings, the number of
 164 synergies (r) was fixed to four synergies. This choice was based on the fact
 165 that the number of synergies used in previous studies varied from one or two
 166 synergies [32] to six synergies [48], for example.

167 Three criteria were investigated: the sparsity of synergy matrix, the num-
 168 ber of channels, and the added noise level. The sparsity of the synergy matrix
 169 $\mathbf{S}_{(m \times r)}$ is investigated since all muscles (channels) may be not activated during
 170 a specific movement at the same time. The sparse synergies were created by
 171 constraining each channel by 40% sparsity level (i.e., a maximum of for chan-
 172 nels being active in each synergy) to ensure that each channel has at least one
 173 non-zero value in the four synergies. This approach would typically avoid hav-
 174 ing channels that are inactive in all 4 synergies as shown in Figure 2a as an
 175 example of sparse synthetic synergies. In comparison, the non-sparse synergies
 176 are non-negative random values between $[0,1]$. Secondly, the effect of dimension
 177 reduction between the generated signal and synergies (basis vectors) is exam-
 178 ined. The number of synergies is fixed to 4 in all settings while the number of
 179 channels are 4 (no dimension reduction), 8 or 12 channels. Finally, the effect of
 180 additive signal to noise ratio (SNR) is compared at three levels: 10, 15 and 20
 181 dB. In total, 10 synthetic datasets are generated, each containing 1000 separate
 182 trials for each setting.

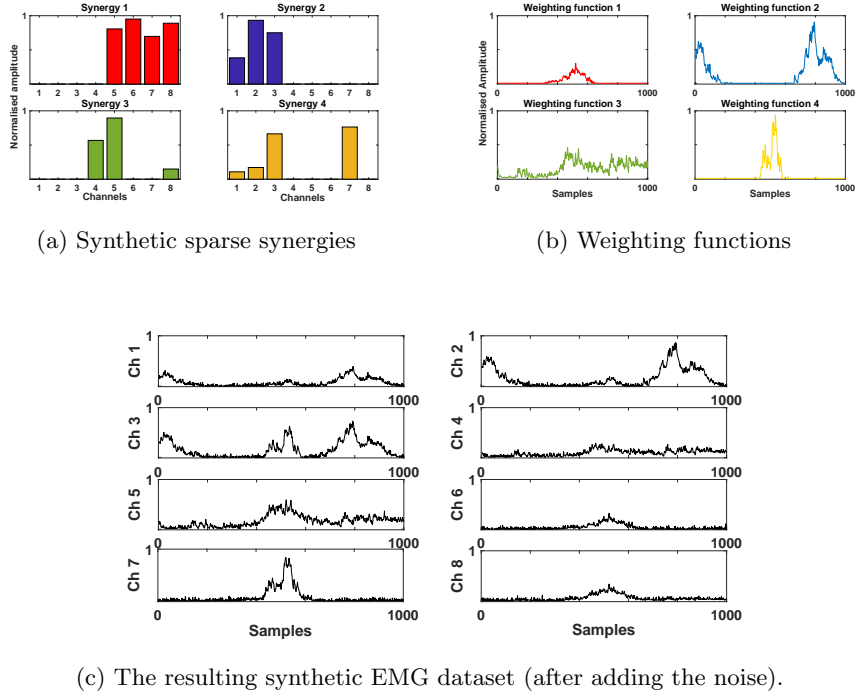


Figure 2: An example of 8-channel synthetic EMG signal (Panel 2c) creation using four sparse synergies (Panel 2a) and their respective weighting functions (Panel 2b) which is a randomly selected real EMG segments with 15 dB SNR.

2.3. Matrix factorisation algorithms

The muscle synergy time-invariant model is approached as a blind source separation problem, where a multichannel EMG signal matrix $\mathbf{M}(t)$ is modelled as a linear mixture of synergies and “source signals”. Therefore, according to equation 1, $\mathbf{M}(t)$ will follow the linear matrix factorisation model as follows

$$\mathbf{M}(t) = \mathbf{S}\mathbf{W}(t) \quad (5)$$

In this context, \mathbf{S} is the mixing (synergy) matrix while $\mathbf{W}(t)$ contains the source vectors (weighting functions) with dimensions number of synergies \times time. The noise is disregarded in equation 5. In order to estimate unique solutions, additional constraints are needed.

PCA constrains the components of the model in equation 5 to be orthogonal,

193 where the first component holds the largest variance and the variance progres-
 194 sively decreases for each component [49]. Here, PCA has been performed using
 195 the “pca” Matlab function (version 2016a).

196 For ICA, the fixed-point algorithm introduced in [50] has been used. Unlike
 197 PCA, ICA attempts to extract independent components by whitening the data
 198 to remove any correlation. Then, it rotates the pre-whitened data to extract
 199 the non-Gaussian components.

200 NMF imposes a non-negative constraint on the extracted factors. The algo-
 201 rithm relies on a cost function to quantify the quality of approximation between
 202 the data matrix \mathbf{M} and its factorised non-negative matrices \mathbf{S} and \mathbf{W} where
 203 $\mathbf{M} \approx \mathbf{S}\mathbf{W}$. Values of \mathbf{S} and \mathbf{W} are updated and optimised to find the local
 204 minima numerically. The Matlab function “nnmf” (version 2016a) was used to
 205 perform the NMF based on [51].

206 SOBI [42] has not been applied to extract muscle synergies before. However,
 207 it is included in this comparison because SOBI utilises the joined diagonalisa-
 208 tion of time delayed covariance matrices to estimate the unknown components.
 209 Therefore, it could reveal more information about the temporal profile of the
 210 EMG activity. Thus, SOBI leads to components that are uncorrelated at those
 211 time delays and, therefore, it is sometimes considered an alternative to ICA,
 212 which is based on higher order statistics. Here, SOBI was performed using
 213 the default 4 diagonalised covariance matrices with the function “sobi” in the
 214 ICALAB package [52].

215 As an illustration, the real 10-channel EMG epoch shown in Figure 1 is
 216 factorised with the four matrix factorisation methods (PCA, ICA, SOBI and
 217 NMF) into two synergy model as shown in Figure 3.

218 *2.4. Factorisation performance comparison using synthetic data*

219 The synthetic data was used to compare the ability of the four matrix fac-
 220 torisation techniques to estimate the muscle synergies in three different settings
 221 (SNR, number of channels and synergies sparsity). The comparison relies on the
 222 similarity between estimated and true synergies using the correlation coefficient

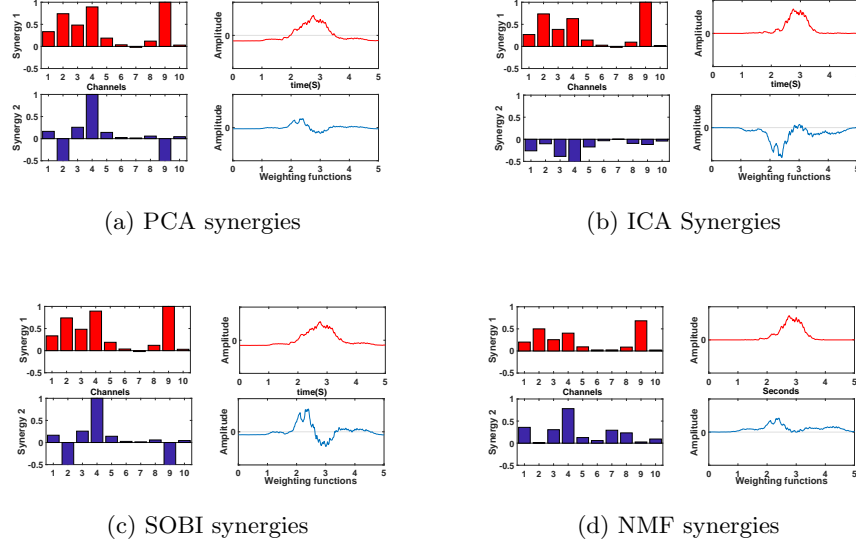


Figure 3: Two-component muscle synergy extracted via the four matrix factorisation methods for the 10-channel EMG signal recorded during wrist extension movement for 5 seconds (Subject 4/repetition 1)

on the basis of full identification of true synergies and similarity level between them. The sequence of this process is shown in Figure 4.

The first step is to match each of the extracted synergies with the true ones by calculating Pearson’s correlation coefficients between them. True and estimated synergies with the highest correlation value are matched together. This matching is done freely and unconstrained. In other words, without forcing a full match (all four estimated synergies matched with all four true synergies) because in some cases two or more estimated synergies have the maximum correlation with the same true synergy. In those cases, the factorisation is not successful since the extracted synergies failed to fully represent all true synergies. Hence, the “fully matched” criterion is the ability of the factorisation method to estimate fully distinctive synergies that match all true synergies without duplication. The success rate for a “fully matched” is computed across the 10 generated datasets. It is used as a metric to judge the ability of extracted synergies to fully represent all the true synergies, since a good factorisation

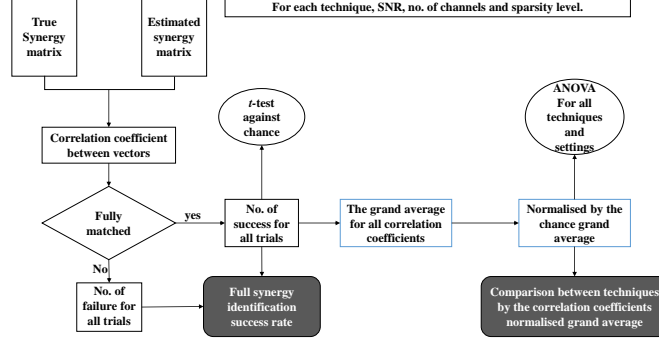


Figure 4: Block diagram for the comparison between matrix factorisation techniques.

would represent all of them.

In order to account to the chance that synergies may be randomly paired, the correlation coefficients between the true synergies and a set of randomly generated synergies are computed and the pairing rates are compared against for each factorisation method using a two-sample t -test with significance level set up at $(p < 0.05)$.

Secondly, the correlation coefficient values for fully identified synergies are averaged for each trial. The grand average is computed for 10000 trials (1000 epochs \times 10 datasets) of each setting combination. Then, it is normalised by the random synergy's correlation coefficients (chance grand average) as baseline removal as the following:

$$Normalised\ grand\ average = \frac{(grand\ average - chance\ grand\ average)}{(1 - chance\ grand\ average)}$$

. The normalised grand average of the correlation coefficients between estimated and true synergies is computed for each matrix factorisation method with all different combination of the 3 settings (SNR levels, number of channels and sparsity). This criterion is an indicator of general factorisation quality. Therefore, we statistically analysed it to compare the factorisation techniques and the effect of all 3 settings using the 2-way ANOVA method with the significance level at $(p < 0.05)$.

251 2.5. Factorisation performance comparison using Real data

252 Since there is no ground truth to compare each technique with for the real
253 data, we compared the techniques regarding their application for prosthesis
254 control. In several studies [31, 53], muscle synergy is used as a feature to classify
255 different hand and wrist movements. Therefore, the factorisation techniques are
256 assessed according to their classification accuracy for the 3 main wrists DoF.

257 To this end, the Ninapro real dataset is divided into training and testing
258 sets with 60% (6 repetitions of each task) of the data assigned to training for
259 each subject. For each factorisation technique, synergies are estimated from
260 training repetitions for each task. Those synergies are used to train k -nearest
261 neighbours (k -NN) classifier ($k=3$ for simplicity). Four classifiers are trained
262 using the training synergies, three of them to classify between 2 tasks of each
263 wrist DoF while the 4th classifier is trained to classify between all 6 tasks. The
264 number of synergies extracted was one for each repetition (two for each DoF)
265 as in [32] to avoid permutation issues. The testing dataset - which contains
266 the other four repetitions of each task - is used to test those classifiers. One
267 synergy is estimated directly from each task repetition in the test set using the
268 four factorisation methods and used to predict the task through the trained
269 classifiers. The classification error count for each DoF is used to evaluate the
270 factorisation techniques.

271 2.6. Number of synergies

272 For the classification accuracy comparison using real datasets, the functional
273 approach to determine number of synergies were chosen. A one-synergy model
274 was applied for EMG activity of each movement. On the other hand, for the
275 synthetic dataset comparison, the number of underlying synergies was known
276 to be four.

277 The generated synthetic dataset can also be used to test the mathemati-
278 cal methods to determine the number of synergies. The minimum description
279 length (MDL) was chosen as an alternative to the explained variance methods
280 as the latter is biased towards PCA since this relies on maximising the explained

281 variance on the first components. The MDL method determine the number of
 282 synergies that could minimise the MDL. For more details please see Appendix
 283 Appendix A.

284 In this study we use the synthetic dataset to test the ability of MDL method
 285 to estimate the required number of synergies across various settings (Sparsity,
 286 noise and channel to synergy ratio). Since four true synergies are used, only
 287 the 8 and 12 channels datasets were investigated as the MDL boundary cannot
 288 estimate number of synergies when it is equal to channels. This is not a prob-
 289 lem in practical applications since the muscle synergy hypothesis implies the
 290 concept of dimension reduction. In addition, three level of SNR (10, 15 and 20
 291 dB) of sparse and non-sparse datasets were explored with 1000 trials for each
 292 combination. The result for correct estimation of synergies number is analysed
 293 via analysis of variance (ANOVA) and multiple comparison of population.

294 3. Results

295 3.1. Number of synergies

296 The model selection method based on MDL was examined with the synthetic
 297 EMG data where the number of synergies are known (four synergies). The MDL
 298 method was tested on 1000 trials for each combination of sparsity, three levels
 299 of noise and two number of channels (8 and 12 channels).

300 The ANOVA shows that sparsity has no significant effect on the estimation
 301 of the correct number of synergies $p > 0.05$, while number of channels has a
 302 significant effect with $[F(1, 11) = 19.94, p = 0.003]$ as 12-channels datasets
 303 performs better than 8-channel signals (shown in Figure 5). As for the level
 304 of noise, the 10 dB SNR had a significantly worse performance than 15 and
 305 20 dB SNR with the effect of noise significant at $[F(2, 11) = 24.22, p = 0.007]$
 306 by 1-way ANOVA. This indicates that, the MDL method for estimating the
 307 correct number of synergies performs better with lower noise and more available
 308 channels, as expected.

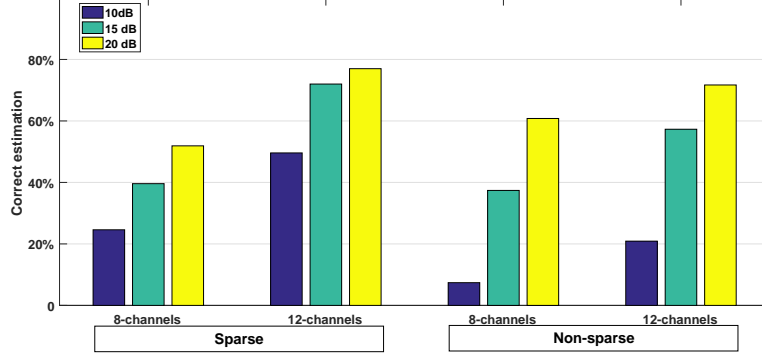
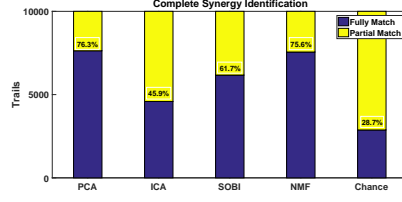


Figure 5: Percentage of correct synergy number estimation using the MDL method across the three settings (noise, number of channels and sparsity).

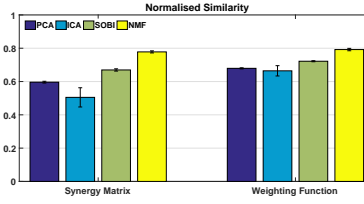
3.2. Factorisation performance comparison using synthetic data

The four matrix factorisation methods were compared on the basis of two criteria: synergy full identification success rate and the normalised grand average of correlation coefficients for the fully identified synergies. The comparison was done on 10000 trials (10 datasets of 1000 trials) for each combination of the three settings (sparsity, SNR and number of channels). An example of one setting of non-sparse, 12-channel with 15 dB SNR is shown in Figure 6. All the four factorisation techniques had converged for all trails except for ICA which failed to converge in 1.48% of the trails.

The four factorisation methods were assessed by their ability to fully identify all 4 true synergies by matching them according to their Pearson’s correlation coefficients values. In order to rule out any statistical chance from it, a two-sample t -test was conducted to compare the success rate of each technique and the randomly generated synergies. All the techniques succeeded to reject the null hypothesis ($p < 0.05$) for all the settings. Hence, there is a significant difference between the matching success rate for each of the matrix factorisation methods and the randomly generated synergies. An example of the success rate for one of the settings is shown in Figure 6a, while the average success rate to fully identify the true synergies for all settings is represented in Figure 7. NMF



(a)



(b)

Figure 6: The results for non-sparse, 12 channels dataset with 15dB SNR. Panel 6a, the success ratio for the factorisation techniques to fully match the true synergies is shown. Panel 6b, the normalised similarity values for each technique single trial with the same settings. Error bars indicate standard deviation.

and PCA are has the highest success rates to fully identify synergies.

The correlation coefficients of the matched synergies were normalised by the random synergy correlation coefficients as shown in Figure 6b. Then the normalised correlation coefficient of synergies (synergy matrix) were averaged across trials. The grand average for each factorisation method was normalised by the chance's grand average. In Figure 8, the normalised grand average (similarity metric) for the four matrix factorisation methods is plotted for all different settings (sparsity, number of channels and noise level). It is worth mentioning that although NMF have the highest similarity for all settings except for the four channel case (the results for the sparse, four-channel setting for NMF are mostly negative). On the other hand, all four algorithms perform worse with four channels (no dimension reduction) with SOBI being the best algorithm among them in this case.

In order to explore the significance of those settings the two-way ANOVA was performed with post-hoc multiple comparison test. The result shows that

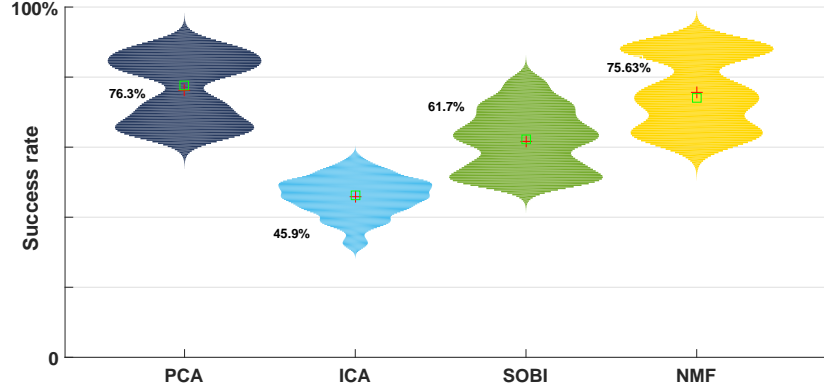


Figure 7: Violin graph for the success rate of full synergy identification for each method across all settings. The mean and median are represented in the Figure as red crosses and green squares respectively.

number of channels and sparsity had a significant effect on the grand normalised average at $[F(2,688)=1364.5, p \leq 0.05]$ and $[F(1,400)=7.35, p=0.007]$ respectively. The multiple comparison test shows that sparse synergies and the higher number of channels show better similarity levels. On the other hand, the noise level fails to reject the null hypothesis. This means that the level of noise used in these experiments did not affect the quality of estimated synergies significantly unlike the sparsity or number of channels. In addition, this was supported by the interaction results, where factorisation methods and number of channels interaction showed a significant effect on the grand normalised average, as well as factorisation method and sparsity interaction. On the contrary, the noise level and factorisation techniques interaction have no significance on the grand normalised average.

The computational efficiency was compared after each technique ran for 100 times on Matlab 9 with Intel core i7 processor(2.4 GHz, 12 GB RAM) and the median value for the running time were computed. PCA and SOBI were the fastest with (0.0012 s and 0.0015 s) respectively followed by NMF with 0.0063 s while ICA was significantly slower by 0.6419 s.

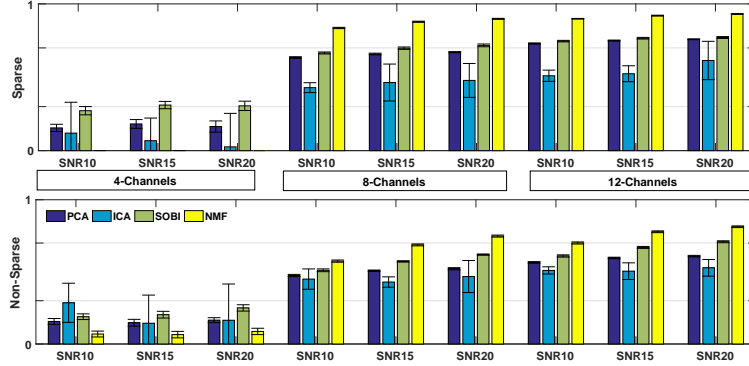


Figure 8: The normalised grand average of correlation coefficients for the fully identified synergies compared across all 3 settings (sparsity, SNR and number of channels) for the 4 matrix factorisation methods. Error bars indicate standard deviation.

3.3. Factorisation performance comparison using Real data

An example of the four matrix factorisation methods is shown in Figure 3 by applying them on 10-channel EMG data. In order to show the similarities and differences in the estimated synergies and their weightings functions of each technique. For example, synergies extracted by PCA and SOBI have similarities in this example since both techniques are based on covariance matrices. The number of synergies needed in this example was chosen to be two according to the MDL method.

In addition, to compare between the matrix factorisation techniques, a one-component synergy was used to train a k -NN classifier ($k=3$) in order to classify between two antagonistic movements (one DoF) for each technique. This was calculated for the three wrist DoFs separately as shown in Table 1. In addition, the same synergies were used to classify between all six movements (three DoFs). The average classification error rate and its standard deviation for the 27 subjects is also represented in Table 1.

4. Discussion and Conclusion

In this paper, we compared the most common matrix factorisation techniques (PCA, ICA and NMF) for muscle synergy estimation alongside SOBI,

Table 1: The classification error count and (error percentage) for each wrist’s DoF (Sample size=216) and all 3 DoFs (sample size=648) across 27 subjects

	PCA	ICA	SOBI	NMF
DoF1 (wrist flexion and extension)	1 (0.46%)	28 (12.96%)	8 (3.70%)	1 (0.46%)
DoF2 (wrist radial and ulnar deviation)	12 (5.56%)	29 (13.43%)	19 (8.80%)	1 (0.46%)
DoF3 (wrist supination and pronation)	7 (3.24%)	31 (14.35%)	18 (8.33%)	5 (2.31%)
All 3 DoFs (all 6 movements)	43 (6.64%)	122 (18.83%)	65 (10.03%)	41 (6.33%)

378 a BSS method that had not been applied for synergy extraction yet. Many
379 studies rely on muscle synergy concept such as myoelectric control and biome-
380 chanical research. However, only two studies [43, 44] compared various factori-
381 sation methods (excluding SOBI) for synergy estimation without investigating
382 the factors that affect the factorisation quality - except for noise.

383 Herein, the comparison was held on real data and synthetic signals generated
384 with known synergies and under different settings. Using the synthetic data we
385 studied the effect of those settings on the muscle synergy extraction for each
386 technique. The sparsity nature of synergies and level of noise was investigated
387 in addition to the number of channels needed to extract the four synthetic
388 synergies. The ability of the four factorisation methods to extract synergies
389 from synthetic data was judged according to two metrics: success rate to fully
390 identify synergies (Figure 7) and the correlation coefficients between true and
391 estimated synergies (Figure 8). Moreover, the synthetic data was used to assess
392 the MDL method to determine number of synergies needed under those three

393 settings.

394 For the real datasets, since there is no ground truth to compare synergies
395 estimated, we compared the factorisation methods according to the ability of
396 their extracted synergies to classify wrist movements (Table 1) as a proof of
397 concept for prosthesis control [30, 40]. PCA and NMF had the best classification
398 accuracy followed by SOBI, while ICA had the lowest accuracy.

399 On the other hand, the synthetic datasets results showed that NMF and
400 PCA had better success rate to fully identify the four true synergies than SOBI
401 and ICA. However, NMF and SOBI had the best normalised grand average of
402 correlation coefficients (similarity level) between estimated and true synergies
403 followed by PCA then ICA. Notably, NMF performed poorly with four-channel
404 datasets when there was not any dimension reduction. In general, all algorithms
405 perform better with higher number of channels compared to synergies, where
406 SOBI was the best algorithm when there is no dimension reduction. There-
407 fore, SOBI would be a relevant algorithm in situations with limited number of
408 electrodes as it is preferable to minimise the number of electrodes for practical
409 prosthesis control [54, 55].

410 The two-way ANOVA showed that the tested range of SNR has no signifi-
411 cance effect on the factorisation performance, although it is noticed that ICA
412 was the most unaffected method to noise according to the multiple compari-
413 son test. On the other hand, sparsity had a significant effect ($p < 0.05$) on the
414 correlation between true and estimated synergies. According to the multiple
415 comparison test, the sparse synergies are easier to estimate by all factorisation
416 methods. Moreover, number of channels shows a significant effect ($p < 0.05$) on
417 the correlation between estimated synergies and true ones. In addition, higher
418 number of channels to number of synergies ratio provides better synergy extrac-
419 tion.

420 Regarding the estimation of the number of synergies, the multichannel EMG
421 signal is reduced into a lower subspace for the purpose of synergy extraction.
422 The estimation of this subspace’s dimension or, in other words, the number of
423 synergies is crucial for the factorisation process. In the literature, there are

424 two main approaches to determine the appropriate number of synergies: the
 425 functional and the mathematical ones. The functional approach determines the
 426 number of synergies according to the myoelectric control requirements such as
 427 assigning two [56, 57] synergies for each DoF. On the other hand, the math-
 428 ematical approach relies on explained variance (using tests such as scree plot
 429 and Bart test) or the likelihood criteria (such as Akaike information criteria and
 430 MDL) [58]. Here, we explored the MDL as an alternative for variance explained
 431 methods. The results show that MDL performs better with higher channel to
 432 synergy ratio. This supports the current challenges for effective synergy iden-
 433 tification with limited number of electrodes. However, further investigation is
 434 needed to compare between different number of synergies estimation methods
 435 using synthetic datasets with various settings.

436 Other limitations are worth noting. The results may be biased towards NMF
 437 due to the non-negative nature of the simulated synergies. However, this choice
 438 is supported by previous studies [40] which suggested the usefulness of NMF
 439 due to the additive nature of the synergies. In addition, further examination is
 440 needed if the setting of EMG acquisition changes dramatically (really bad SNR,
 441 much higher number of channels, etc.) to evaluate the validity of our conclusions
 442 in those settings. Finally, since various studies employ the muscle synergy in
 443 prosthesis control, a simple approach (k -NN classifier) was used in this paper as
 444 an example to guide synergy application and to support the synthetic results.
 445 We treated this part of the study as a proof of concept. Additional work is
 446 needed with more advanced techniques and variety of tasks and movements.

447 In conclusion, this paper compared matrix factorisation algorithms for mus-
 448 cle synergy extraction and the factors that affect the quality of estimated syn-
 449 ergies. Our findings suggest that the presence of sparse synergies and higher
 450 number of channels would improve the quality of extracted synergies. When
 451 the number of channels equal to synergies (no dimension reduction), SOBI per-
 452 formed better than other methods although the performance was still poor in
 453 this case. Otherwise, NMF is the best solution for robust synergy extraction
 454 when number of channels/muscles is higher than the required muscle synergies.

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672 **Appendix A. Minimum description length (MDL)**

673 The MDL method for determining the number of synergies is performed by
 674 calculating the maximum likelihood estimates of factor loading matrix \mathbf{A} and
 675 the unique variances diagonal matrix $\mathbf{\Psi}$ according to the factor analysis model

$$\mathbf{C} = \mathbf{A}\mathbf{A}^T + \mathbf{\Psi} \quad (\text{A.1})$$

676 where \mathbf{C} is the covariance matrix of $\mathbf{M}_{m \times n}$ the multi-channel EMG signal matrix
 677 with m channels and n samples.

678 This is done for different number of synergies (r) between $1 \leq r \leq \frac{1}{2}(2m+1-\sqrt{8m+1})$
 679 in order to minimise the MDL. The boundary for r is set by comparing
 680 the number of equations with unknowns in order to have an algebraic solution
 681 for equation A.2.

$$L(\mathbf{A}, \mathbf{\Psi}) = -\frac{1}{2} \left\{ \text{tr}(\mathbf{C}(\mathbf{\Psi} + \mathbf{A}\mathbf{A}^T)^{-1}) + \log(\det(\mathbf{\Psi} + \mathbf{A}\mathbf{A}^T)) + m \log 2\pi \right\} \quad (\text{A.2})$$

$$\text{MDL} = -L(\mathbf{A}, \mathbf{\Psi}) + \frac{\log n}{n} \left(m(r+1) - \frac{r(r-1)}{2} \right) \quad (\text{A.3})$$

682 The number of synergies r are selected to minimise the MDL value in equation
 683 A.3.